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Privatizing Climate Change Policy: is there a public benefit?

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Abstract:

The Chicago Climate Exchange (CCX) and the Carbon Disclosure Project (CDP) are two private voluntary initiatives aimed at reducing carbon emissions and improving carbon management by firms. I sample power plants from firms participating in each of these programs, and match these to plants belonging to non-participating firms, to control for differences between participating and non-participating plants. Using a difference-in-differences model to control for unobservable differences between participants and non-participants, and to control for the trajectory of emissions prior to program participation, I find that CCX participation is associated with a decrease in total carbon dioxide emissions for participating plants, but not carbon dioxide intensity. The CDP is associated with a decrease in carbon dioxide intensity, but not total carbon dioxide emissions.

Keywords: Voluntary environmental programs; climate change policy; Chicago Climate Exchange; Carbon Disclosure Project; difference-in-differences model; propensity score matching

JEL codes: Q50, Q54, Q58, D80, C23

Privatizing Climate Change Policy: is there a public benefit?[1]

1. Introduction

Voluntary environmental agreements between industry and government have received significant attention in the academic literature over the past decade. While researchers have begun to understand when these types of programs can be effective at improving environmental quality, private initiatives on the part of non-governmental institutions and for profit corporations have received less attention, and it is unclear what the tradeoffs are for these types of initiatives and whether voluntary initiatives by private industry can lead to improvements in environmental quality and enhance the efficiency of environmental policy.

More specifically, this research seeks to determine the relationship between the approach of different voluntary environmental policy programs (VEP) and the effectiveness and efficiency of these approaches. To assess this research question, I examine an information provision approach – the Carbon Disclosure Project - and a cap-and-trade approach – the Chicago Climate

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Exchange - to greenhouse gas reduction in power plants in the United States. Using a unique dataset where I calculate greenhouse gas emissions from the heat content of fuels, I use a difference in differences model to measure program effectiveness and efficiency by employing a two-stage model that controls for selection bias, and then measure the change in carbon dioxide emissions and carbon dioxide intensity against a control group.

This research offers several unique contributions to the understanding of firm behavior, regulation, and environmental policy. First, while significant research has been conducted on the efficacy of public voluntary programs, very little research has addressed the effectiveness of private approaches to voluntary programs. Recent research has suggested that benefits from public voluntary programs may accrue to both participating firms, and non-participating firms (Lyon & Maxwell 2007). While firms may improve environmental behavior, non-participants also improve environmental behavior suggesting that the program is ineffective, or that contagion exists between participants and non-participants (Lyon & Maxwell 2007; Rivera, et al. 2006). These spillover effects of voluntary policy may be due to the motivations of government actors to share program benefits across industry in order to reach environmental goals. As a result, current analyses of public voluntary programs may be mis-specified. By examining private voluntary programs, which may be more likely to keep program benefits as a club good, it is more likely that the effects of these programs can be isolated.

Second, voluntary programs can take advantage of a variety of policy tools that result in tradeoffs regarding program effectiveness and efficiency. While many studies have examined the impacts of individual programs, less is known about the comparative effectiveness and efficiency of varying levels of coercion in environmental regulation. While voluntary programs are typically regarded as non-coercive, voluntary programs can assume the characteristics of many different types of policy tools (Richards 2000). This study seeks to help compare information provision approaches – a relatively low coercive method, where firms do not commit to any explicit emissions reductions, and cap-and-trade approaches – a highly coercive method in voluntary environmental policy, where firms commit to a specific change of behavior.

Finally, as legislators consider policy responses to climate change, it is increasingly apparent that a variety of policy tools and approaches will be necessary to tackle climate change (Victor, et al. 2005). Much research exists regarding voluntary approaches for addressing toxics, however, it is unclear whether lessons regarding voluntary agreements in toxics will be applicable to greenhouse gases, due to financial incentives to reduce energy costs (Morgenstern & Pizer 2007). While some studies examine the impacts of voluntary carbon reduction programs, this area has received much less attention in the literature than toxics (Lyon & Kim 2007; Morgenstern & Pizer 2007; Welch, et al. 2000). This research will give policy-makers and researchers a better understanding of the potential and role for voluntary programs to help address climate change and greenhouse gas reduction.

This paper proceeds as follows. First, I detail several approaches to voluntary environmental policy tools, and discuss private approaches to voluntary environmental policy (section 2). Second, I discuss my research design, including the construction of my sample and dataset, as well as the methodology for evaluating the effectiveness of voluntary environmental policy (section 3). Third, I present and discuss the quantitative results of the study (section 4). I conclude with recommendations for policy design as well as for future study of voluntary environmental policy (sections 5 and 6).

2. Background and theory

2.1. Policy tools and voluntary environmental policy

This research hopes to demonstrate the comparative effectiveness and efficiency of different approaches to environmental policy. Policy tools in environmental policy can encompass a wide array of models that vary based on the amount of coercion employed by government. Traditional command-and-control regulation often specifies limits for pollutants and can even specify methods and technology for pollution control. Market-based regulation removes either the limits to pollution – by incentivizing emissions reduction through taxes or subsidies, or removes the regulations on how pollution was to be reduced, by establishing tradable property rights through a cap-and-trade system. Even less intrusive are labeling or information disclosure requirements, which seek to reduce information asymmetry between the producer and the consumer.

Voluntary environmental policy is not a unique policy instrument, but rather, can take the form of any of an array of types of policy instruments (Richards 2000). While studies have examined individual voluntary environmental programs, few studies have sought to quantitatively compare the effectiveness and efficiency of different approaches to voluntary policy. Understanding the tradeoffs in effectiveness and efficiency of voluntary environmental policies is essential for improving the design and implementation of these policies. While the pressure placed on firms involved in voluntary policy may be different than in mandatory policy, this research seeks to compare two private voluntary programs that employ different policy tools as mechanisms of addressing carbon emissions.

2.2. Private approaches to voluntary environmental policy

While the literature regarding voluntary environmental programs has examined a multitude of programs, most have focused on public voluntary agreements, and of those – most research has focused on programs where government negotiates a pollution reduction target with an industry association. Much less is known about private voluntary initiatives to improve environmental quality (Arimura, et al. 2008; Dasgupta, et al. 1997; Lyon, et al. 2010; Potoski, et al. 2005a, 2005b, 2005c; Prakash, et al. 2006).

Private voluntary initiatives can take several forms. An NGO or non-profit organization can commit organizations to voluntarily improving environmental behavior. Examples of this type of arrangement include International Standard for Organization (ISO) certification, which includes the implementation of environmental management practices, the Forest Stewardship Council Certification (FSC), which promotes the responsible management of forests, and the Carbon Disclosure Project (CDP) which asks firms to disclose carbon management practices as well as carbon related risks and opportunities. While public voluntary agreements are driven by government initiative, these programs are driven by consumers, investors, and supply chain managers. Investor led programs rely on market pressures to induce behavior change and threaten non-participants with financial penalties (Ananathanarayanan 1998; Feldman 1996; Hamilton 1995).

A second type of private voluntary initiative includes firm-led initiatives, which include unilateral measures on the parts of individual firms, or collaborative efforts by a group of firms (Lyon, et al. 2004). These efforts, like public voluntary environmental programs, may be initiated in order to help firms gain experience with new types of regulation, improve public relations, or reduce the prospect or enforcement of more costly mandatory policy (Khanna 2001; Lyon & Maxwell 2004).

Several reasons exist for studying private approaches to environmental policy. First, while researchers and policymakers are beginning to get a better understanding of public voluntary initiatives, less is known about the effectiveness of private initiatives.

Second, because there is less government oversight of these programs, it is unclear what their impacts may be. These programs may not be responsive to public interests – rather, they fulfill the needs of their stakeholders. While carbon reduction is in the public interest and may contribute to social welfare, voluntary initiatives may only lead firms to reduce carbon when it is in the private interest of stakeholders, and is likely to be under-provided by the market. While part of the promise of voluntary environmental policy was a movement towards self-regulation, it is important to understand the extent to which these programs can have positive impacts on environmental governance.

Third, public voluntary programs have been difficult to study due to possible spillover effects – as government institutions have the incentive to disseminate best practices to non-participating firms (Lyon & Maxwell 2007). Because government agency goals include improving environmental quality as much as possible, government officials may disseminate best practices for energy efficiency to non-participating firms, late joiners to a voluntary agreement, and other stakeholders. Private initiatives are often able to limit benefits of participation to participants – making participation akin to a club good (Potoski & Prakash 2005c). This characteristic of private initiatives may help solve the specification problems inherent in analyzing public voluntary agreements.

2.3. Addressing greenhouse gas emissions through VEP

While an enormous body of literature exists regarding the effectiveness of VEP on reducing toxics, greenhouse gases may provide a number of different incentives, and may be handled differently by firms. In the rational model of voluntary environmental policy, firms undertake voluntary environmental action to deflect the implementation or enforcement of more stringent mandatory regulation in the future (Lyon & Maxwell 2004). Firms may also participate as part of a rational cost-benefit calculus where firms gain reputational or marketing advantages, experience with new regulations or new mechanisms such as carbon trading. There is mixed evidence for the effectiveness of voluntary policy under this model. While initial analyses concluded that these programs could be effective and in particular could reduce toxic releases, recent research has suggested that participants in these programs reduced toxics or greenhouse gases no more than non-participants in the programs (King, et al. 2000; Lyon & Maxwell 2007; Morgenstern, Pizer, et al. 2007; Vidovic, et al. 2007; Welch, et al. 2000).

Greenhouse gases depart from toxics along several criteria. While toxics are considered an unpriced byproduct of the production process, greenhouse gases are primarily the result of fossil fuel combustion. Because energy costs are already included in the costs of production, voluntary reductions of greenhouse gases should not be expected. Most research on voluntary greenhouse gas reduction programs have not found substantial reductions as a result of the voluntary programs (Lyon & Kim 2007; Morgenstern & Pizer 2007; Welch, et al. 2000). However, these evaluations are subject to some of the criticisms discussed above.

A contrasting view of voluntary environmental programs suggests that firms are boundedly rational, and may have difficulty incorporating energy costs into production costs (Matisoff 2010). Considerable variation exists regarding the technological and investment decisions by manufacturers and utilities (Kolk, et al. 2005). Firms – and in particular regulated electricity generators – may be able to vary fuel mixes in order to reach competing production, cost, and environmental goals (Welch, et al. 2009). Thus, substantial leeway may exist for firms to reduce greenhouse gases. Evidence that investments in capital can improve profitability and environmental outcomes supports this hypothesis (Boyd, et al. 1999; Shadbegian, et al. 2006).

3. Research Design: Assessing the Effectiveness of VEP

3.1. Sample

The sample for this study consists of electric utility power plants in the United States to evaluate two private voluntary environmental programs. First, the Carbon Disclosure Project (CDP) is a private voluntary initiative designed to promote improved management of carbon by pressuring firms to report their carbon emissions, and describe their carbon strategies and carbon related risks and opportunities. The CDP began in 2000 with a London-based coordinating secretariat for institutional investors to gain insight to climate related risk of Fortune 500 publicly traded corporations by standardizing reporting procedures for climate change related activities. The results of the first cycle of the project, released February 17th, 2003, were endorsed by approximately 35 investors controlling $4.5 trillion in assets. By the end of 2007, the CDP had grown considerably and was funded and run by over 385 institutional investors including major players such as Goldman Sachs, Merrill Lynch, and state pension funds, controlling over $40 trillion in assets. By 2007, over 2,400 firms were targeted and 1,300 firms responded to the survey (CDP4) reporting on various aspects of carbon management (Kolk, et al. 2008). Of the Fortune Global 500 companies, CDP4 resulted in a 91% response rate and 72% answered the questionnaire in full. The CDP ranks firms based on the quality of their responses and rewards transparent firms with acknowledgement in their Carbon Disclosure Leadership Index. Firms are allowed to make their responses public, or can keep responses limited to the institutional investors that fund the program.

The logic for the project is simple: “addressing the climate change challenge depends on a dialogue, between shareholders and corporations, supported by high quality information. Companies need to articulate their position in a coherent way to an increasingly sophisticated set of stakeholders” (PricewaterhouseCoopers 2008). Further, the project notes that a business can only manage what it measures – the first step in good management is good measurement. While the program seeks to have independently verifiable emissions data, about 35 to 50 percent of participants have independent verification and about 65 percent of responding firms make their direct emissions publicly available. Because there are no explicit contractual obligations involved in the CDP, and firms can choose whether or not to respond, how much information to provide, and whether or not they make their responses public, the CDP represents a less-coercive approach to VEP.

The second program represents a more coercive approach towards private voluntary climate change policy. The Chicago Climate Exchange is a private, for-profit venture where firms agree to reduce carbon emissions by one percent per year. Members represent a variety of industries and organizations, and also include offset providers and aggregators. Members make a voluntary but legally binding commitment to meet annual greenhouse gas reduction targets. Those who reduce below the targets can bank or sell excess allowances; those who emit above the targets comply with their contractual obligations by purchasing permits on the market. The exchange also provides independent, third party verification through the Financial Industry Regulatory Authority (FINRA, formerly NASD). While the program seeks to improve facilitate greenhouse gas allowance trading through price transparency and environmental integrity, the program does not make any emissions information available to the public or to investors. Trading began in 2003; the program boasts over 300 members, including offset providers.

3.2. Data

Three types of data had to be collected to analyze the effectiveness of these programs. First, plant level data, including CO_2 emissions and non-fuel expenditures were collected as the dependent variables. Electricity generation and plant construction year were also collected at the plant level. Second, because participation in voluntary programs is determined at the firm level, firm level data were collected, including firm size (measured as revenue) and whether or not a firm is publicly traded. Finally, state characteristics relating to the regulatory climate of each state were coded and collected to control for varying levels of regulations and incentives that might impact regionally situated electricity producers.

3.2.1. Plant level data

Fuel use data was used to estimate carbon emissions. To calculate carbon dioxide emissions, the amount of each type of fuel used in each power plant was multiplied by the heat rate, and the DOE regulations were used for the 1605b voluntary program in order to determine carbon dioxide emissions for each power plant reporting fuel use to the Energy Information Administration.[2] Plant level data were collected from 1994 – 2007 for approximately 5,000 prime movers[3] (engines or turbines), which was then compiled to generate fuel use data for approximately 1,000 power plants in the United States, totaling 14,393 plant-year observations. Plant level data were compiled with the assistance of Indianapolis Power and Light from the Velocity data suite, which relies primarily on data collected from EIA forms 861, 412, 906, 920,

[2] Because the 1605b regulations only have carbon dioxide emissions information for major types of fuel, I used the closest match for rare types of fuel.

[3] Prime movers are the engines or turbines in a power plant. Each power plant may be composed of multiple prime movers. Fuel use is reported to the EIA at the prime mover level.

923, and FERC form 1.[4] In addition, variables were collected for the purposes of calculating additional dependent variables and in order to control for plant characteristics. These variables include plant capacity, electricity generation, year of construction, and non-fuel operating expenditures.[5]

3.2.2. Firm level data

Firms were coded as public or private using Compustat, Google Finance, and other search engine methods. Firm revenue data were collected from the Compustat database.[6]

3.2.3. State level data

State regulatory data and information regarding renewable energy and energy efficiency programs were compiled from the Database for State Incentives for Renewable Energy (DSIRE) and individual state energy offices, as well as the Environmental Protection Agency website (DSIRE 2009). The changing regulatory environment in each state may have a relationship with the electricity generation decisions made by individual power plants. Previous research has demonstrated the number of energy programs active in a state to be the product of political ideology, geographic resources, economic resources, and carbon-intensive industry present in a

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[4] Because fuel use data, data containing plant characteristics, and firm level and state level data were contained in separate datasets, data were merged into one large dataset using plant ID numbers, and operator ID numbers.

[5] Missing plant construction year data and capacity data were periodically encountered. In these cases data was carried down from previous years.

[6] Following Berry and Fording (1997), I imputed missing data for firms missing a year to several years of revenue data using Stata's linear trending missing data function (Berry, et al. 1997). These observations were less than 2% of the total observations.

state (Matisoff 2008). Similarly to Hall and Kerr (1991) and Gray and Shadbegian (2003), who employ a count of laws regulating toxic waste in the states in order to construct a TOXIC index, measuring the regulatory stringency of each state, I count the total number of renewable energy and energy efficiency programs active in a particular state, for each year, as an indicator of regulatory activity in each state (Gray, et al. 2003; Hall, et al. 1991). This was compiled through the DSIRE website, as well as via e-mails and phone calls to individual state energy offices. While this measurement is an imperfect measurement of the regulatory stringency of each state, it is a good time-variant indicator available of the changing energy regulatory environment at the state level.[7] The EPA website and state energy offices were used to determine whether or not states had active restructuring in each year.

3.2.4. Obstacles and Challenges

Due to the nature of this work, a variety of tradeoffs had to be made to secure such a complete and detailed dataset. First, plant data is only available for power plants that have greater than 25 megawatt capacity. Second, unregulated electricity generators did not have to report plant data beginning in 2003. I was able to determine which plants had closed after 2002, and which had ceased to report data based on whether the plant had reported fuel use, which was still required after 2002. Third, plants that do not have reported fuel use do not appear in the dataset, eliminating many renewable energy plants. Fourth, deregulated plants that began operation in 2003 or later may not have appeared in the dataset, due to changes in reporting requirements. Finally, nuclear plants and plants operated by universities were also eliminated

[7] For more information about the types of energy policies included in this measure, see the DSIRE database and Matisoff (2008). For more information about the reliability of this measurement, see Matisoff (2008).

from the dataset to achieve greater unit homogeneity. Altogether, the dataset totals 13,552 plant-year observations, or 968 power plants over 14 years.

4. Methodology

This study employs propensity score matching, to control for static observable differences between the treatment group and control group, and a difference-in-differences model to control for unobservable static differences between the treatment group and the control group. I test for robustness by estimating effects with a fixed effects model as well. These results are included in the appendix. Below, I review the literature and methodology in further detail.

Non-experimental methods of assessing program effectiveness are susceptible to a variety of biases (LaLonde 1986). These include selection biases based on the propensity to join a program, the distributions of propensity to join a program, and “pure” self-selection, when individuals’ self selection behavior is based on information that researchers cannot observe, or is caused by inter-temporal dependence of an outcome variable (Heckman, et al. 1997; Heckman, et al. 1999; Jung, et al. 2010). Selection bias based on the observable propensity to join a program can be controlled for using propensity score matching (RH Dehejia, et al. 2002; Heckman, et al. 1997; Jung & Pirog 2010). “Pure” selection bias can be decomposed into three sources of bias, which have various implications. First, individuals with higher returns from the program may be more likely to participate. Second, individuals with lower opportunity costs to join might be more likely to participate. The third source occurs when low opportunity costs of joining are correlated with program outcomes (Jung & Pirog 2010). Of these sources of pure selection bias, the second and third sources tend to underestimate treatment effects, while the first source overestimates treatment effects (Jung & Pirog 2010). The second source of pure selection bias can be controlled for using a difference-in-differences approach, and overall, fixed effects estimators and difference-in-difference estimators perform well in reducing bias, and in particular, the effect of treatment on the treated (TT) (Jung & Pirog 2010).

Following Heckman et al. (1997), and similarly to Lyon et al. (2011), this study employs propensity score matching and a difference in differences approach, which has been demonstrated effective at eliminating bias, especially when it is due to temporally invariant omitted variables – that is, static differences between the treatment group and control group (Heckman, et al. 1997). It is an extremely effective way of measuring average program effects under much weaker assumptions than matching alone (Heckman, et al. 1997). The effects of the treatment on the treated can be identified under the relatively weak mean independence assumption, formulated in terms of P(X), where X represents the observable conditions that lead to program participation and D represents whether or not plants participate in a specific program. For more information on this identification strategy, or alternative identification strategies, see Heckman et al. (1997), or Heckman and Robb (1986).

$$E(Y_0 \mid P(X), D = 1) = E(Y_0 \mid P(X), D = 0) \qquad [1]$$

In order to fulfill this assumption and identify the causal effects in the difference-in-differences approach, at least one of the matching variables (X) must be uncorrelated with the outcome variable Y (in this case, the annual change in plant-level carbon dioxide emissions) (Caliendo, et al. 2008). For more information on this identification strategy, or alternative identification strategies, see Heckman et al. (1997), or Heckman and Robb (1986). A more thorough discussion of the consequences of this approach follows below.

4.1. Matching

Because plants participating in a voluntary program may be systematically different than plants not participating in a voluntary program, it is necessary to establish a control group of plants for each of the treatment groups. Creating a matched control group can serve as a method to form a quasi-experimental contrast between a treatment and control (Morgan, et al. 2007), and can serve as a form of nonparametric preprocessing that can improve the reliability of parametric estimates (Ho, et al. 2007). Because of the large size of the dataset, and multiple time period nature of the dataset, I chose to use a nearest-neighbor propensity score matching method, which has been demonstrated to reduce selection bias (Heckman, et al. 1996). Using this method, I match plants based on the probability that plants are participants in each voluntary program, given plant, firm, and state characteristics. Following Morgenstern et al (2007), participating plants are then matched, without replacement, to the non-participating plant that has the closest probability of joining the voluntary program.

$$Pr[joining = 1 / \sum x] = \frac{exp(a + b_1 x_1 + b_2 x_2 + b_n x_n)}{1 + exp(a + b_1 x_1 + b_2 x_2 + b_n x_n)} \qquad [2]$$

Plants from each program were matched with a sample of non-participating plants, based on participation status in 2007.[8] A one to one nearest neighbor match was conducted using the Stata user generated program psmatch2, using a logit regression (Leuven, et al. 2003). For each program, plants were matched by psmatch2 using the likelihood of participation in each voluntary program, based on whether or not the firm is publicly traded (1 = yes), the year of plant construction, the capacity of the plant (in megawatts), the number of state energy programs

[8] Once firms chose to join the CDP, they rarely, if ever, left. Matching based on 2007 data ought to reduce selection bias, as it accounts for firm future expectations regarding the regulatory environment, firm growth, and expected plant openings and closings when deciding to join the CDP during program years 2004 – 2006.

active, the parent company size (measured as the natural log of millions of dollars in revenue), and whether or not utility restructuring was active in a state (1=yes).

In order to fully identify the causal effects in the difference-in-differences approach below, it is important to have at least one predictor in the propensity score matching equation that is correlated with the decision to participate, but is uncorrelated with plant level carbon dioxide emissions. The *parent* company size (revenue) ought to be uncorrelated with *plant* level annual change of carbon dioxide emissions. Because each holding company owns multiple plants – and in many cases operates in multiple industries – there is little reason to believe that the size of the corporate parent is correlated with plant-year observations of changes in carbon dioxide emissions. However, the size of the corporate parent is one of the strongest predictors of whether or not a firm joins a voluntary environmental program, making it a good instrumental variable for this purpose.

Participation decisions in voluntary environmental agreements are made by corporate parents, rather than individual plants, and larger firms have consistently participated in voluntary environmental agreements more regularly than smaller firms (Khanna 2001). Revenues for the holding company in 2007 measured firm size. Investor owned utilities are much more likely to participate in voluntary environmental agreements because the CDP specifically targets large, publicly traded firms, while the CCX is comprised primarily of publicly traded firms. Finally, because of varied state regulatory activity, plants that operate in states with more regulatory activity related to energy may be more likely to participate in voluntary initiatives.

Unmatched participating or non-participating plants were discarded from the sample, leaving 5,180 plant-year observations for the Carbon Disclosure Project, and 2,744 plant-year observations for the Chicago Climate Exchange. While matched samples allow me to assume that there is no difference between the treatment group and the control group, it is still possible that unobserved differences within the treatment group and control group exist (Moffit 1991; Morgan & Winship 2007).

Once matching has occurred, the expected outcomes for each the control group, and the treatment group are the same, given the observable differences in the treatment group and control group. I test this assumption using a Hotellings T-squared test statistic on the joint equivalence of the covariates between the treatment and control groups (Caliendo & Kopeinig 2008). However, this method does not control for unobserved heterogeneity within each plant, nor does it control for changes in conditions over time. These issues will be addressed in the difference-in-differences approach discussed next.

4.2. Difference in differences approach

To control for unobserved heterogeneity or omitted variables in matching process as well as changes in conditions at each plant over the study period, I take the first difference of my outcome variable *y* (carbon emissions, then total non-fuel expenditures) and each of my control variables λ over time period *s* (1994-2007), where *x* (program participation) is not differenced and is a dummy variable that denotes program participation in year *t* (Allison 1990; Moffit 1991; Morgenstern, Pizer, et al. 2007). Thus, I estimate the change in the dependent variable as a function of program participation and changes in conditions.

$$\Delta_s y_{it} = \alpha + \sum \beta_{it} X_{it} + \sum \theta_{it} \Delta_s \lambda_{it} + e_{it} \qquad [3]$$

where: $\Delta y_{it} = y_{it} - y_{i(t-1)}$ and $\Delta \lambda_{it} = \lambda_{it} - \lambda_{i(t-1)}$

This equation is estimated using ordinary least squares, with robust standard errors clustered on the panel variable *i*.

The difference in differences approach controls for any static heterogeneity between the treatment group and the control group, assuming that participants and controls have the same distributions of unobserved attributes; that they have the same distributions of the observed attributes; and that they are in a common economic environment (Heckman, et al. 1997). The time-variant control variables control for observable conditions that change over time including changes in the state regulatory environment (measured as the number of energy programs in a state each year, and whether or not a state has active electricity restructuring), firm growth rate, and changes in plant-level electricity generation. Thus, the difference in differences approach does not control for any time-variant unobserved heterogeneity, such as a change in firm philosophy over time, or a change in firm management over time, and assumes constant program effects over time (or alternatively calculates an average program effect over time). Because the panel consists of 14 years of data, in order for time-variant unobserved heterogeneity to impact the measurement of program effects, it must occur simultaneously with the program participation. That is, the difference-in-differences approach only fails to control for unobserved heterogeneity when it is time-variant and occurs simultaneously to the decision to participate in the voluntary program.

The matching method is used for both the Chicago Climate Exchange and Carbon Disclosure Project. The difference in difference method is repeated for each program for plant level CO_2 emissions (in metric tons), and plant level total non-fuel costs (in dollars). Each model is estimated with and without a control for the quantity of electricity generation.

5. Results

<*insert Table I about here*>

In this section, I present the results from the rigorous methodology discussed above. Additional results employing other specifications follow in the Appendices.

As demonstrated by Table I, I predict 10 to 13 percent of the variation of a plant's probability of joining each voluntary program. While parameter estimates seem to support existing theory regarding participation in voluntary environmental policy, the standard errors are incorrect, due to different levels of measurement of the independent variables, and correlation across observations. Thus, it is not possible to directly interpret parameter estimates as hypothesis tests on the independent variables. [9]

Because the Chicago Climate Exchange is a small program, and the CDP is such a large program, many unmatched observations were eliminated from the sample (see table III). For the CCX, 98 plants in the sample participated in the program, allowing these to be paired with the 98 plants that most closely resembled those that participated in the program. In contrast, only 185 plants belonging to publicly traded firms *did not* participate in the CDP, leading to the exclusion of participating plants. While other methods of matching such as kernal matching, matching with replacement, and weighted matching would have allowed for more data to be used in a difference of means test, these methods would not have been easily compatible with a longitudinal difference in differences model, which is the more important step in this methodology.

The matching exercise had dramatic effects on the sample selection (see table II). For the Chicago Climate Exchange, the control group was much more likely to be publicly traded, firms were smaller, plant capacity was greater, plants were slightly newer, and states were much more

[9] While the standard errors are not correct – the parameter estimates are unbiased and consistent. This allows for substantive interpretation of the parameter estimates, but not for causal relationships.

likely to have undergone restructuring, and to have adopted numerous energy programs than compared with the full sample. For the Carbon Disclosure Project, non-publicly traded plants were dropped from the sample, and control group plants were part of smaller firms, of larger capacity, were newer in construction, and were more likely to have active state restructuring, as well as more state energy programs and regulations.

Recent literature suggests that because poorly matched samples may create bias in estimated program effects, the matched samples should be tested for balancing to reduce bias and ensure that the matching process sufficiently controls for observable differences between the treatment and control group (Smith, et al. 2005a, 2005b; Smith, et al. 2009). A variety of tests exist to check for balancing, and these methods have received criticism due to the inconsistency of results (Lee 2006; Smith & Zhang 2009), and whether or not balancing tests are necessary (R Dehejia 2005).

While a balancing test is not essential for this sample, as the difference in differences model will control additional heterogeneity by examining only the within unit changes over time, following Smith and Petra, 2005b, I conduct a Hotelling T-Square balancing test to demonstrate the similarity of treatment group and control group after matching. The Hotelling T-Square test is essentially an F-test on the joint equivalence of the covariate means of the treatment group and control group and can be conducted in Stata. As Table II demonstrates, the treatment group and control group have extremely similar means and standard deviations, and the F test fails to reject the null hypothesis that the means of the two samples are jointly equivalent. Both the CCX sample and the CDP sample appear balanced by both measures, even before within differencing.

<insert Table II about here>

<insert Table III about here>

<insert Table IV about here>

Table IV demonstrates the impact of program participation in either the Chicago Climate Exchange or the Carbon Disclosure Project on changes in plant level emissions, compared to what would have occurred had program participation not occurred. Specification 1 for each program does not control for changes in electricity output for each plant, while specification 2 controls for electricity output, effectively measuring the changes in carbon intensity of greenhouse gas emissions. In all specifications, the program participation variable is not differenced, and represents a simple dichotomous measurement of total program effect.

Participation in the Chicago Climate Exchange is associated with, on average, a cumulative 79,468 metric ton decrease in carbon emissions, compared to the matched control group and the emissions trajectory prior to program participation. Once electricity generation is controlled for, the CCX does not appear to have a statistically significant impact on carbon dioxide intensity.[10] Because the average plant in the sample emits about 2.2 million tons of carbon dioxide per year and has participated in the CCX for 4 years, this is equivalent to a 20

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[10] Due to the trading nature of CCX program requirements, standard errors are likely to be inflated, because individual power plants do not have specific emissions reductions requirements. Some power plants ought to increase electricity production and carbon emissions, while others ought to decrease carbon emissions. Nevertheless, the program parameter estimates ought to be unbiased.

thousand ton decrease in total emissions per year, or .9 percent decrease in total emissions, per year, for four years.

A fixed effects model (see Appendix B) estimates dramatically greater decreases of total CO_2 emissions and CO_2 intensity. Other specifications (see Appendices A & C) that do not match samples, also demonstrate a statistically significant decrease in total emissions, but not carbon dioxide intensity, of the CCX. While the results for total carbon dioxide emissions are largely consistent – painting a picture of decreased emissions associated with participation in the CCX, the results for carbon dioxide intensity are inconsistent – dependent upon the specification of the model. Fixed effects models suggest that CCX participants decreased the carbon intensity of production, while difference-in-differences models suggest that there was no improvement of CO_2 intensity associated with CCX participation. These results likely differ because a fixed effects model accounts for variation across observations, whereas the difference-in-differences model only accounts for within variation and provides a much more conservative estimate of program effectiveness. If firms shift production to more efficient power plants, this result may not be captured by the difference-in-differences specification for carbon intensity.

Participation in the Carbon Disclosure Project, in contrast, does not seem to impact total carbon emissions, though may lead to reductions in carbon intensity. Controlling for electricity generation, CDP participants have decreased carbon emissions by 24,730 tons. The average length for participation in the CDP is 2.69 years, suggesting that CDP participants have each reduced their carbon emissions by about 9,000 tons per year, or about 0.4 percent per year, for 3 years, in comparison to non-participating firms, and when electricity generation is controlled for. Similar to results for the CCX, fixed effects specifications (both with matched samples and unmatched samples) generate coefficients with larger magnitudes (see Appendices B & C). An unmatched difference-in-differences model does not demonstrate statistically significant decreases in total carbon dioxide emissions or intensity (see Appendix A). This lack of statistical significance may indicate downward bias that was controlled for by the matching process. If the cost of participating in a voluntary program is low, adverse selection likely results in underestimated parameter estimates of program effects (Jung & Pirog 2010).

6. Discussion

The numerous manipulations of the data make it difficult to discern the impact of different specifications and matching techniques. The model has been run with a variety of specifications in order to reduce the concern related to the matching process and the various types of selection bias that is likely present in the model.

While there is some inconsistency across model specifications, the most robust specification using the best econometric techniques, reported in table IV, indicates that the CCX resulted in decreases of total carbon emissions, but not the carbon intensity of electricity production. In contrast, the CDP resulted in a slight decrease in the carbon intensity of electricity production, but not total carbon emissions. This result suggests that CCX participants reduced electricity generation in fossil fuel powerplants by shifting electricity generation outside of the sample (to renewable energy plants, nuclear plants, or hydro-electric plants), or by simply reducing total electricity demand. In contrast, CDP participants may have increased total electricity production, but produced this increased electricity more efficiently (through boiler upgrades, and more efficient powerplants). While these results may be surprising, they are less surprising when viewed through an institutionalist lens and in the context of the program requirements.

The CCX, viewed from an institutionalist perspective, is highly coercive. It requires emissions reductions (roughly equivalent to what was observed in the matched sample), and commits firms via contract law to those reductions. It does not ask firms how they achieve those reductions, and allows them to trade emissions permits in order to meet reduction requirements. While firms are audited, they disclose very little information to the public.

In contrast, the CDP may be coercive, and investor pressure may force many firms to participate in the CDP, but it does not require behavioral change or specific emissions reductions. Rather, firms are rewarded by investors for transparency and their overall strategy related to carbon. The CDP may simply reward firms that can appear pro-active in carbon management.

Because the CCX is much more coercive in nature, it is to be expected that CCX participation will be narrower, yet produce deeper reductions per firm, while the CDP, with voluntary disclosure rules, might produce broader participation, but shallower reductions. Interestingly, because of the breadth of participation in the CDP, the total amount of carbon reduction achieved by the CDP may be similar to or even greater than the CCX. With 98 power plants participating in CCX, and 515 power plants participating in the CDP, the total annual emissions reduction attributable to power plants participating in the CCX is about 2 million tons per year, while power plants participating in the CDP total 2.8 million tons of carbon reduction, based on the parameter estimates reported in Table IV.

Nevertheless, caution is needed when interpreting these parameter estimates. Program participation is measured by a dummy variable, which measures the decision to participate in a voluntary environmental program, but also captures any unobservable changes in firm behavior that directly temporally coincide with the decision to participate. Changes made by a firm prior to participation should not impact estimated program effect. However, the measurement of program participation can capture a broader array of behavioral changes by a firm than simply the decision to participate. It seems likely that any decision to participate in a voluntary environmental program was accompanied by changes in how firms decide to manage carbon; however, these changes are not observable, and are captured by the program participation measurement.

With CCX emissions permits trading with a value between $0 and $2, it seems unlikely that drastic changes in firm behavior occurred due to a price on carbon permits. It seems much more likely that firm management recognized carbon emissions as a growing liability, chose to participate in the voluntary trading program, and chose to shift management practices towards increased efficiency and fuel switching when these changes were not particularly costly. Participation in the CCX is associated with firms identifying and taking advantage of low cost emissions abatement opportunities. Evidence from other studies suggests that low and no cost efficiency improvements may be widely available, and it is possible that participation in voluntary programs can help firms identify these opportunities. Because regulated power plants can pass along the costs of efficiency investments to consumers, these firms may not be cost minimizers, but instead may have been able to build in modest carbon emissions reduction goals into medium term investment decisions.[11]

Conversations with firm managers support these conclusions. According to one manager, "joining the Chicago Climate Exchange was part of an effort to start to become more attuned to

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[11] Results, not reported here, showed increases in non-fuel expenditures for both the CCX and the CDP compared with control groups. These results were not statistically significant, likely due to capital depreciation practices leading to large swings in reported capital investments.

our carbon impact, gain experience with carbon trading and prepare for changing regulatory conditions. We have made a lot of subtle changes in the way carbon is managed – from experimenting with hybrid cars and trucks to efficiency upgrades at power plants, where we try take a long-term view…"[12]

CDP results seem to reinforce these findings. While the CDP has no emissions reduction requirements and firms simply report their carbon management strategies, CDP participants decrease their emissions and emissions intensity associated with electricity production, and increase their non-fuel expenditures. Conversations I have had with program participants and CDP officials suggest that the decision to participate in the CDP reflects behavioral changes made by firm managers aimed at improving the management of carbon.

7. Conclusion

These results highlight several tradeoffs for the design of voluntary environmental programs and their effectiveness. First, while the CCX appears to have achieved deep reductions in carbon dioxide amongst a small number of firms, the Carbon Disclosure Project may have had a broader impact. This highlights the tradeoffs between high participation in a program and the types of emissions reductions that can be achieved voluntarily.

Second, this research highlights the tradeoffs of privately run voluntary environmental programs. While much research in the VEP area is pessimistic regarding the potential for voluntary programs to solve environmental problems or drive real changes in corporate behavior, these results suggest that firms that participate in these voluntary programs improve their environmental behavior in comparison to firms who are not participating. While it is not clear that the program participation drives these behavioral changes, voluntary environmental

[12] Conversation with Electric Utility Firm Manager July, 27, 2009.

programs may provide a reward or recognition for firms that are already planning to improve environmental behavior, and a way for firms to signal to the market that they take environmental behavior seriously. This reward to firms – especially when provided by the private sector, and not by the government, seems like an exceptionally low price to pay for improvements in environmental behavior. While there is a danger of greenwash – allowing firms to represent themselves as more "green" than they actually are, there is similarly a danger of discouraging firms from participating in environmentally beneficial activities. Participation in the CCX or CDP may simply demonstrate a firm's commitment towards improved management practices, or may serve as a justification for firm managers to pursue strategies that reduce carbon emissions and intensity.

Firms are faced with a variety of strategic options when attempting to address carbon management. Firms can invest in efficiency and technology improvements, engage in fuel switching, purchase or create offsets from developing countries, or do nothing. Previous research suggests that many firms prefer to pursue business-as-usual outcomes, and that many firms severely discount the benefits of efficiency investments (Matisoff 2010; Welch & Barnum 2009). Firms that participate in the CCX or CDP appear to depart from the business-as-usual trajectory, and have chosen to invest in cost-effective carbon reduction strategies.

These results may understate changes due to the CCX or CDP. This sample only measures changes in fossil fuel consumption, and does not measure changes in the increase of renewable electricity, or other changes that might occur outside of the sample. The difference-in-differences model only measures within plant changes of behavior, when there is likely to also be across-plant changes in behavior (captured by the fixed effects models). In addition, electric utilities are potentially the most rational of industries, with simple production processes that make it easy to consider carbon dioxide emissions in electricity production. In contrast, manufacturers face more complex production processes and decision-making, and are more likely to pursue business-as-usual under uncertain conditions.

8. Notes

i. Because the 1605b regulations only have carbon dioxide emissions information for major types of fuel, I used the closest match for rare types of fuel.

ii. Prime movers are the engines or turbines in a power plant. Each power plant may be composed of multiple prime movers. Fuel use is reported to the EIA at the prime mover level.

iii. Because fuel use data, data containing plant characteristics, and firm level and state level data were contained in separate datasets, data were merged into one large dataset using plant ID numbers, and operator ID numbers.

iv. Missing plant construction year data and capacity data were periodically encountered. In these cases data was carried down from previous years.

v. Following Berry and Fording (1997), I imputed missing data for firms missing a year to several years of revenue data using Stata's linear trending missing data function (Berry, et al. 1997). These observations were less than 2% of the total observations.

vi. For more information about the types of energy policies included in this measure, see the DSIRE database and Matisoff (2008). For more information about the reliability of this measurement, see Matisoff (2008).

vii. Once firms chose to join the CDP, they rarely, if ever, left. Matching based on 2007 data ought to reduce selection bias, as it accounts for firm future expectations regarding the regulatory environment, firm growth, and expected plant openings and closings when deciding to join the CDP during program years 2004 – 2006.

viii. While the standard errors are not correct – the parameter estimates are unbiased and consistent. This allows for substantive interpretation of the parameter estimates, but not for causal relationships.

ix. Due to the trading nature of CCX program requirements, standard errors are likely to be inflated, because individual power plants do not have specific emissions reductions requirements. Some power plants ought to increase electricity production and carbon emissions, while others ought to decrease carbon emissions. Nevertheless, the program parameter estimates ought to be unbiased.

x. Results, not reported here, showed increases in non-fuel expenditures for both the CCX and the CDP compared with control groups. These results were not statistically significant, likely due to capital depreciation practices leading to large swings in reported capital investments.

xi. Conversation with Electric Utility Firm Manager July, 27, 2009.

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Table I: Generating a Matched Sample for the Chicago Climate Exchange: predicting participation in the Chicago Climate Exchange and the Carbon Disclosure Project in 2007

Logistic Model	CCX	CDP
Number of Observations	966	700†
LR Chi^2	66.60***	101.83***
Pseudo R^2	.1050	.1259
Publicly Traded Firm (1=yes)	1.823 (.479)***	†
Firm Level Revenue (ln$000,000)	-.305 (.102)***	.821 (.099)***
Plant Capacity (MW)	.00021 (.00016)	.00002 (.00013)
Year of Construction	-.00587 (.00525)	-.0135 (.0045)***
Active State Restructuring (1=yes)	1.011 (.264)***	-.240 (.2197)
Total State Energy Programs (#)	.0379 (.0134)***	.03387 (.0133)***
Constant	9.058 (10.356)	19.88 (8.81)**

* represents significance at the $\alpha = .10$ level
** represents significance at the $\alpha = .05$ level
*** represents significance at the $\alpha = .05$ level

† because only publicly traded companies participated in the CDP, the matching software excludes non-publicly traded companies from the sample

Table II: Means and Standard Deviations of Matched Samples, with Hotelling T-Square Balancing Test

Chicago Climate Exchange Matched Sample (98 pairs)

Variable	Full Sample Mean	Full Sample Standard Deviation	Control Mean	Control Standard Deviation	Treatment Mean	Treatment Standard Deviation
Publicly Traded Firm (1=yes)	.72	.45	.83	.380	.88	.329
Firm Level Revenue (ln$000,000)	8.83	1.19	8.17	1.61	8.28	.98
Plant Capacity (MW)	642	679	700	739	691	697
Year of Construction	1968	22.00	1968	19.57	1963	21.04
Active State Restructuring (1=yes)	.413	.493	.76	.432	.70	.458
Total State Energy Programs (#)	15.03	8.54	20.77	10.46	19.85	8.49

Two Group Hotelling T-Square = 5.38

F Statistic = .8737; p-value = .5153

Carbon Disclosure Project Matched Sample (185 pairs)

Variable	Full Sample Mean	Full Sample Standard Deviation	Control Mean	Control Standard Deviation	Treatment Mean	Treatment Standard Deviation
Firm Level Revenue (ln$000,000)	8.83	1.19	8.33	1.38	8.51	.89
Plant Capacity (MW)	642	679	693	640	741	678
Year of Construction	1968	22.00	1971	20.89	1976	20.70
Active State Restructuring (1=yes)	.413	.493	.41	.492	.36	.481
Total State Energy Programs (#)	15.03	8.54	14.42	8.45	13.37	6.30

Two Group Hotelling T-Square = 8.50

F Statistic = 1.683; p-value = .1378

Table III: Observations in Dataset and for each program

Program	CCX	CDP
Number of initial plants	966	966
Initial plant-year observations	13,558	13,558
Matched pairs	98	185
Total plant-year observations after first differencing	2,548	4,810

Table IV: Chicago Climate Exchange versus the Carbon Disclosure Project: Difference-in-differences model, Effect of Participation on ΔCO_2 emissions (metric tons), OLS parameter estimates shown, clustered standard errors in parentheses

Model	CCX1	CCX2	CDP1	CDP2
Observations	2534	2534	4810	4810
F Statistic	2.71**	184.15***	4.44***	90.30***
R-Squared	.0022	.7222	.0029	.6016
Program Participation	- 79,468* (41,052)	- 7,386 (13,917)	- 15,712 (18,304)	- 24,730** (10,056)
Publicly traded	33,918 (20,175)*	7,511 (8,305)		
ΔState Restructuring	- 17,870 (17,365)	- 185 (9,619)	3,447 (15,939)	11,010 (9,507)
ΔFirm Revenue (ln $000,000)	- 11,430 (25,464)	21,470** (8,865)	17,849 (25,928)	- 16,151 (15,322)
ΔState Programs	- 4,035 (4,273)	- 1,139 (1,861)	- 17,697*** (4,503)	- 5,069* (2,875)
ΔMWh		.8067*** (.0270)		.7409*** (.0354)
Constant	4,127 (22,122)	-2,964 (8,614)	30,393*** (9,075)	- 393 (5,904)

* represents significance at the $\alpha = .1$ level
** represents significance at the $\alpha = .05$ level
*** represents significance at the $\alpha = .01$ level

Appendix A: Chicago Climate Exchange versus the Carbon Disclosure Project, all complete observations: Difference-in-differences model, Effect of Participation on ΔCO_2 emissions (metric tons), OLS parameter estimates shown, clustered standard errors in parentheses

Model	Model 1	Model 2
Observations	12,402	12,402
F Statistic	5.78***	124.51***
R-Squared	.0019	.6469
CCX Program Participation	-43,986** (19,955)	-10,062 (13,441)
CDP Program Participation	-2,000 (11,033)	-4,021 (6,372)
Publicly traded	18,112*** (5,951)	8,581 (3,740)**
ΔState Restructuring	-9,669 (7,808)	6,783 (4,531)
ΔFirm Revenue (ln $000,000)	-262 (13,165)	3,084 (5,874)
ΔState Programs	-9,984*** (2,489)	-4,747*** (1,416)
ΔMWh		.7264*** (.0282)
Constant	20,445 (5,114)***	-3,686 (3,081)

* represents significance at the $\alpha = .1$ level
** represents significance at the $\alpha = .05$ level
*** represents significance at the $\alpha = .01$ level

Appendix B: Chicago Climate Exchange versus the Carbon Disclosure Project: Fixed-Effects model

Model	CCX1	CCX2	CDP1	CDP2
Observations	2743	2743	5179	5179
F Statistic	20.76***	940.59***	17.05***	1,239***
R-Squared	.0120	.9696	.0126	.9682
Program Participation	- 583,378*** (90,816)	- 421,116*** (54,729)	60,506* (34,313)	- 38,104* (22,875)
Total State Energy Programs	769 (2,883)	2,879 (1,736)	177 (2,558)	- 2,250 (1,703)
State Restructuring	88,253* (46,264)	33,487 (27,866)	3,717 (31,141)	68,459*** (20,745)
Total Firm Revenue (ln $000,000)	108,161*** (22,785)	25,297* (13,774)	98,346*** (14,033)	- 31,044*** (9,381)
Total MWh		.7366 (.0110)***		.6591*** (.0085)
Constant	1,379,015*** (168,439)	189,861* (102,956)	1,534,300*** (109,28)	- 399,768*** (74,150)

* represents significance at the $\alpha = .1$ level

** represents significance at the $\alpha = .05$ level

*** represents significance at the $\alpha = .01$ level

Appendix C: Chicago Climate Exchange versus the Carbon Disclosure Project, all complete observations: Fixed-Effects model

Model	Model 1	Model 2
Observations	13,357	13,357
F Statistic	58.25***	3,263.67***
R-Squared	.0431	.9737
CCX Program Participation	-318,811*** (35,548)	78,339*** (22,458)
CDP Program Participation	-123,376*** (18,359)	20,046* (11,588)
Total State Energy programs	2,777** (1,388)	-2,451 (875)***
State Restructuring	-4,409 (17,544)	59,182*** (11,060)
Total Firm Revenue (ln $000,000)	97,672*** (9,973)	36,878*** (6,297)
Total MWh		.6438*** (.0047)
Constant	1,311,108 (72,861)***	316,131 (46,460)***

* represents significance at the $\alpha = .1$ level
** represents significance at the $\alpha = .05$ level
*** represents significance at the $\alpha = .01$ level